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Tools for validating causal and predictive claims in social science models

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Abstract

To better understand and describe the world around them, and ultimately produce theories that can facilitate better decision making or policy interventions, social scientists need to be able to create, analyze, and validate social, political, and economic models that include causal and predictive elements. Causality is, however, notoriously difficult to analyze. This is especially true in social science due to the complexity of the phenomena being studied. To address this complexity, we describe a suite of causal/predictive analysis techniques adapted from a variety of social, natural, and computational science applications, specifically chosen for their unique applicability to the problems of analyzing temporally offset causes and effects. In particular, we describe four methods for analyzing predictive/causal claims: (1) Granger causality is a well-established method from econometrics that can identify relationships between temporally offset causes and effects when the offsets are fixed; (2) forward-only dynamic time-warping (DTW) addresses uneven temporal offsets; (3) convergent cross mapping (CCM) can be used to analyze bi-directional causality produced by the feedback relationships present in many social systems; (4) finally, we describe a novel feature-based qualitative pattern-recognition approach to identify and explain qualitative causal/predictive relationships that don't fit more traditional correlation-based analysis techniques. Social scientists can use this mix of analytic techniques to validate (or more-precisely, to invalidate) their causal/predictive hypotheses and produce more robust understandings of complex systems. We present prototype software implementations of these analytic techniques and demonstrate the efficacy of our proposed approaches.

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Keywords: Causal models; Predictive models; Model validation; Granger causality; Convergent Cross Mapping; Dynamic time warp

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1. Introduction

When building scientific models of the world, including models of socio-political systems, it is crucial to be able to represent, reason about, and (to the extent possible) validate causal and predictive relationships in those models. In, fact, it is largely the ability to capture these sorts of relationships that makes models useful for predicting the future and enables policy makers to use them to make informed decisions. While human social science experts often have good insights about the causal/predictive relationships in their field of study, they quickly become overwhelmed by the amount and complexity of data necessary to validate their models or tease out more subtle relationships, so we propose to look to automated/computational tools to support the human experts in this task.

We focus on two types of analysis, both of which combine automated/computational analysis of data and human expertise. In the first type of analysis, model invalidation, the human scientist has developed a model of a sociopolitical phenomenon that they want to compare against available data in an attempt to find flaws with the theory (in practice, proving a theory is correct from data is impossible in many cases, especially when using only observational data, so we focus on analysis techniques that attempt to invalidate the theory and find flaws with the expert's theory). In the second type of analysis, we use automated techniques to identify and hypothesize novel causal/predictive relationships that have not been provided by the human expert. This is a form of machine learning or data mining, which is notorious for identifying spurious relationships. In this case, the role of the human expert is to vet the automated hypotheses, refine them, and decided how they belong in their theoretical model of the world.

Causal/predictive analysis is notoriously challenging, especially in social science where there are numerous, complex, and subtle causal/predictive linkages to understand, and where controlled experiments are difficult, meaning we must rely on observational data. Further, existing tools are helpful, but not sufficient for addressing the task at hand. For instance, existing quantitative/statistical tools that are often used to analyze data (e.g., STATA, R, SAS, and Excel) lack the analytical depth and social-science focus necessary to identify casual relationships and provide deeper understanding of social theories. At the other end of the spectrum, qualitative researchers often view causality as deterministic, rather than probabilistic. This approach finds possible causes/predictors for some phenomenon *A* of interest, such that without *B*, *A* would not have occurred. By focusing on analysis of counterfactuals, potential causal/predictive candidates can be invalidated by a single deviation from the overall pattern [1]. However, these approaches have difficulty selecting or ruling out competing causal/predictive links [2].

In exploring automated causal/predictive-analysis techniques and the weaknesses of many existing tools, we have identified three properties that make causality analysis particularly difficult in social science research: (1) the temporal nature of causation means that causes and effect can be separated in time (and by non-uniform amounts), making correlation analyses ineffective; (2) it is challenging to tease apart causes and effects in cases of bi-directional or cyclic causality; and (3) qualitative features and effects are difficult to capture in quantitative models.

We have not identified any technique that addresses all of these problems. Therefore, rather than focusing on any one approach, we introduce a suite of causal/predictive analysis techniques adapted from a variety of social, natural, and computational science applications. Each has its own strengths and weaknesses, and has been specifically chosen for its applicability to the challenging causal/predictive patterns in social science research. Social scientists can use these analytic techniques, either individually or in combination, to (in)validate their hypotheses and produce more robust understandings of causal/predictive relationships in complex systems. Note that we do not address the interesting and challenging problem of teasing apart causality and prediction. The models of interest include both predictive and causal elements and the proposed techniques work for both as long as we use them properly.

2. Challenges of complex causal/predictive patterns

The complexity of social and political systems poses a challenge for researchers attempting to discover or validate causal/predictive linkages. We identified several properties of social systems that are particularly challenging to analyze using traditional techniques. We believe these properties also provide opportunities to leverage new insights from a variety of causal/predictive analyses to thoroughly analyze social science theories.

1. *Temporal offsets.* The temporal nature of causation can be both challenging for correlation-based analysis methods and powerful for teasing apart causes from effects. Intuitively, effects cannot precede causes in time.

Current quantitative approaches to analyzing causation based on statistical analyses often address *correlation* as opposed to *causation* [3]. These methods, however, do not account for the temporal gaps between causes and effects, so correlation values or parameters often do not accurately reflect the strength of a causal/predictive relationship and cannot distinguish a clear sequence to determine cause from effect. Many phenomena do not exhibit fixed temporal offsets, either because of actual variability (e.g., an increase in crime might happen anywhere from 6 to 12 months after an uptick in unemployment), or due to sampling rates. These variable offsets make it difficult to identify causal/predictive relationships from data even using advanced time series models.

2. *Bi-directional causality.* Some systems have variables that interact causally in both directions. A simple example is a cyclic predator-prey system where changes in either population will cause a reaction in the other. For example, a decrease in the prey population will cause a decrease in the predator population, which will subsequently cause an increase in the number of prey. Existing methods in both qualitative and quantitative approaches have difficulty representing and validating bi-directional causality. When these effects are offset in time, analysis can be even more challenging, because correlations can be masked in the observed data.
3. *Qualitative features and effects.* Not all models of social or political systems have simple, quantitatively measurable relationships. For instance, if a period of social stability precedes a period of economic growth there may be little statistical correlation between these variables. In fact, correlation-based analyses may actually make this relationship more difficult to discern because the relevant concepts encompass complex combinations of values that must be related to occurrences in another variable. Despite these measurement challenges, these patterns are still associated with qualitatively meaningful concepts that are important to capture and reason about.

3. Model (in)validation and causal/predictive-hypothesis generation

In this section, we present several methods for analyzing causal/predictive relationships. These techniques from a variety of social, natural, and computational domains were chosen for their applicability to the challenges identified above, but are not an exhaustive list. Rather, this suite is the starting point for a battery of tools to help facilitate the identification of and/or the invalidation of complex dependencies that might otherwise be missed, assumed away, or taken for granted, and rule out spurious relationships that might not hold under the given conditions.

3.1. Granger causality for analyzing temporal offsets in causal/predictive relationships

We begin with Granger causality, a statistical technique familiar to many researchers, but worth including for its ability to address temporal aspects of causality and prediction. Granger causality [4,5] was introduced for time series analysis in economics to deal with the inherent temporal ordering implied by causality. Granger causality makes two assumptions: (1) the effect does not precede the cause, and (2) the causal variable provides information about the effect that would otherwise be unavailable. Granger causality is a multivariate auto-regressive process [6], where we compare the results of regressing a variable against time-lagged versions of itself and the causal condition [7].

3.1.1. Definition 1 (Granger cause)

The temporal variable X Granger causes temporal variable Y iff $P(Y_t \mid Y_{t-1}^{t-L}) \neq P(Y_t \mid Y_{t-1}^{t-L}, X_{t-1}^{t-L})$ where L is the maximum time lag, a_i, b_j are parameters in a linear combination, ϵ_1, ϵ_2 are error terms, and

$$P(Y_t \mid Y_{t-1}^{t-L}) = \sum_{l=1}^{L} a_l Y_{t-l} + \epsilon_1 \quad (1)$$

$$P(Y_t \mid Y_{t-1}^{t-L}, X_{t-1}^{t-L}) = \sum_{l=1}^{L} a_l Y_{t-l} + \sum_{l=1}^{L} b_l X_{t-l} + \epsilon_2 \quad (2)$$

A variable *X* is a Granger cause of *Y* if *Y* can be better predicted using the histories of *X* and *Y* than just of *Y* alone. Granger causality focuses on the predictive power of causal relationships and does not attempt to separate causation from prediction [8]. Validating (or invalidating) a causal relationship using Granger causality can be done through hypothesis testing. If equation (2) is statistically more accurate than equation (1) using an *F* statistic, then a Granger-causal relationship between *X* and *Y* can be considered valid for prediction.

3.2. Dynamic time warping for uneven temporal relationships

In social and political systems, variability in human behavior and infrequent data sampling can produce uneven temporal delays or additional artifacts, making causality difficult to validate as temporal offsets between causes and effects (or predictor and predicted) vary over time. For example, suppose researchers hypothesize that lower employment rates cause an increase in crime anywhere from 6 to 12 months in the future. The causal/predictive link may be verified in some cases of interest, but may be difficult to generalize due to the temporal inconsistencies.

To validate these uneven causal/predictive linkages, we borrowed and extended the dynamic time warping (DTW) algorithm from gait recognition [9,10]. DTW has traditionally been used to identify a person's gait from two motion curves, recognizing the correlated pattern of movement (i.e., the characteristics of someone walking slowly and quickly should be the same, even though the time between steps may be compressed or extended). DTW compares the two time series to find the optimal alignment by "warping" one series—that is, stretching or shrinking it along its time axis to align the two curves. From a technical perspective, DTW computes a *minimal warp path*, which identifies the minimum amount of stretching or shrinking required to produce the highest possible correlation.

3.2.1. Definition 2 (Warp path)

Given two time series X and Y of size n and m, a warp path W is a sequence $W=w_1, w_2, \ldots, w_k$ where k is the length of the path and each element $w_k = (i, j)$ represents a mapping between point i in X with point j in Y. The optimal warp path minimizes the sum of distances between the mapped points

$$argmin\ Dist(W) = \sum_{k=1}^{k=K} Dist(w_{ki}, w_{kj}) \qquad (3)$$

where $Dist(W)$ is the distance of warp path W and $Dist(w_{ki}, w_{kj})$ is the distance between point i in series X and point j in series Y.

Because causality can only impact the future, we have enhanced DTW to handle the one-directional case in a new algorithm ForwardDTW. Rather than matching points by warping the time series data in both directions, ForwardDTW only matches the points in X with future values of Y. ForwardDTW allows us to use DTW to analyze causal relationships with uneven time lags—the smaller the warp distance between X and Y, the stronger the causal/predictive link. A user can specify this threshold to determine when a relationship will be considered invalid. Again, DTW may be most valuable from the perspective of invalidating causal/predictive assumptions or indicating circumstances from a large collection of cases when the insights of a causal/predictive hypothesis do not hold, identifying possible candidates for further in-depth case analysis or suggesting refinements to the existing model.

3.3. Convergent cross mapping for bi-directional causality

Granger causality and DTW can identify or validate causal/predictive relationships with complex temporal interactions. However, many social systems contain feedback relationships, where dependency is bi-directional. For example, declining economic output may increase levels of political violence, which further depress the economy. These causal relationships may be intuitive for social scientists, but are difficult to validate in actual data, where correlation analyses (as well as the previous two techniques described) can completely obscure this cyclic linkage.

Convergent cross mapping (CCM) [11], a recent advance in biological studies, can help analyze cyclic causal models. This method can be adapted to model social and political systems, providing a new opportunity to generalize cyclic causal theories. To use CCM, we assume some underlying dynamic, generative process that can be "projected" on to the variables of interest, X and Y. This projection is a set of vectors for variables X and Y called the "shadow manifolds," essentially estimating *how* the unobservable process generates the observed values.

3.3.1. Definition 3 (Shadow attractor manifold)

For a time series variable X, the shadow attractor manifold M_X consists of points $x(t) = (X(t), (X(t-\tau), X(t-2t), \ldots, X(t-E\tau))$ where τ is a sampling time lag and E is the manifold dimension.

For subsets of time series X and Y of length L, we can construct manifolds M_X and M_Y. CCM will then determine how well local "neighborhoods"—small regions of M_X—correspond to neighborhoods in M_Y. If X and Y are causally linked, there will be a one-to-one mapping between points in M_X and M_Y. To create this cross mapping, we use a neighborhood in M_X to predict the values of contemporaneous points in M_Y and compute the correlation ρ between the predicted values. If a causal relationship exists, predictions of Y from X (and vice versa) will improve as the amount of data (L) increases, i.e., the mapping of X and Y will converge to perfect predictability $\rho = 1$.

3.4. Qualitative feature-based analysis

The previous approaches have focused on how to use quantitative data to generalize human-generated causal/predictive hypotheses or further validate correlational analyses. However, some causal/predictive models require the development of qualitative theories to interpret the complex interactions between variables. In these cases, the interesting properties of a social or political system are not descriptive of a single value of some variable in the dataset, but may comprise a context-sensitive pattern of values.

While it is certainly possible to capture some of these qualities statistically (e.g., through controls in multivariate regressions), causal/predictive interactions *between* these qualitative patterns may be difficult to express. Often, the data series themselves will not be related in terms of correlation-based measures, despite obvious relationships in qualitative features. For example, suppose "stability" in the unemployment rate produces a decrease in crime. The raw data will exhibit little or no correlation, but can be explained as the interaction of two qualitative features.

To help social scientists identify and analyze causal/predictive relationships that are more readily described as qualitative features than as strictly quantitative relationships, we borrow a technique from signal processing called *featurization*. Featurization is the process of identifying "interesting" segments of a time series and associating them with a qualitative concept that can be used in a causal/predictive theory. For example, a researcher may first search through an economic time series and select periods of "economic instability," then search a criminal activity time series to extract periods of "increasing crime." By featurizing the data into qualitative patterns, researchers can analyze causal/predictive relationships between variables that exhibit little or no quantitative correlations.

To support this approach, we developed a structural featurization "language" using six common morphologies (or shapes) that can comprise qualitatively meaningful patterns in a time series [12]. More complex patterns can be created by combining multiple elements of this language into compound concepts. For example, a single "cycle" of economic activity may be an upward spike followed by a downward spike. An entire time series can be represented as a sequence of these components, which can then be chosen by the researcher for more in-depth analysis.

Once a time series has been mapped to a sequence of qualitative features, it is possible to analyze the causal/predictive links. For instance, if a model for a particular city indicates that increases in crime (C) follow periods of economic instability (E) (within some time window), we can acquire additional time-series data related to crime and economic activity, convert the series into qualitative features related to "increases in crime" and "economic stability" and search for cases where instances of C are not preceded by Es, where Es are not followed by Cs, and where the specified pattern is actually found in the data.

4. Experimentation and evaluation: Validating a causal model of poverty and violent conflict

The analysis techniques described above provide methods that social scientists can use to validate—or, more precisely, invalidate—their hypotheses. Using a variety of causal/predictive analysis techniques makes it possible to characterize these complex relationships, as well as identify places where models need further refinement or exploration. To illustrate the efficacy of this approach, we have implemented prototypes of the Granger causality, DTW, CCM, and qualitative featurization/analysis algorithms as part of our research software framework called the Model Analyst's Toolkit (MAT). MAT [13, 14, 15, 16] was developed for social scientists and provides tools for exploring and visualizing data as well as for creating, refining, and validating models; a beta version is freely available to the academic and government research communities.

As a case study, we demonstrate a representative exploration of the causal/predictive relationship between

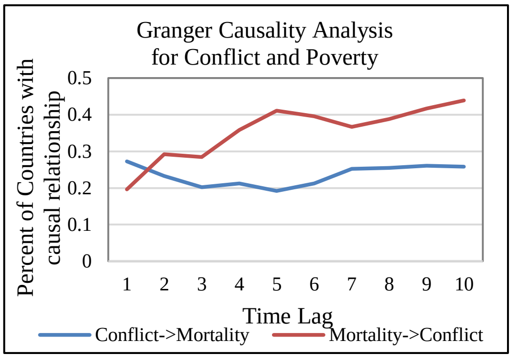

Fig. 1. Results from Granger causality analysis with increasing time lag.

poverty and conflict. A large body of literature exists that explores the “conflict trap”—the process whereby countries get stuck in a repeated pattern of violent conflict and economic underdevelopment [17]. There have been several studies evaluating the causal/predictive link between these two features using standard statistical approaches, with some finding evidence for poverty driving societies into conflict [18,19], while others [20] indicate that civil conflict may be the cause of depressed economic growth. Using the methods described in the previous section, we can better untangle and characterize this relationship and gain insight into the processes that lead to the conflict trap.

The choice of data is itself a challenge for causal/predictive analyses, as the complex and abstract concepts of “poverty” and “conflict” are difficult to represent as measurable variables. To measure conflict we use the UCDP/PRIO dataset [21], which tracks the incidence and intensity of global armed conflict between 1946 and 2013. To capture the notion of poverty, which is not merely a measure of income, but also of relative well-being, we use two variables from the World Bank World Development Indicators dataset [22]—infant mortality rate, measured as the number of infants per thousand live births that die each year, and GDP, to measure the overall level of development. We consider conflict as both a categorical variable ranging from 0 to 3 indicating the intensity of a conflict in a given year, and as a numerical value with counts of the battle deaths due to conflict within a country. We focused on the timeframe from 1960-2013 as both data sets were more complete for this time period.

In our first experiment, we analyzed the relationship between poverty and conflict using Granger causality, varying the time lag between 1 and 10 years. Out of the 100 countries under study, we found strong evidence that conflict causes poverty in about 30% of the cases with a time lag of 1 year, as shown in Fig. 1, with strength of the causal linkage degrading slightly as the time lag increased. Interestingly, there is also strong evidence of a causal relationship from poverty to conflict, but this actually consistently *increases* as we stretch out the time lag. This result may indicate the nature of conflict and poverty as persistent conditions with longer duration impacts, but may also be due to uneven time lags that cannot adequately be captured by Granger causality.

For our second experiment, we used CCM to further characterize the causal relationship between conflict and poverty. Social processes are often best described by complex dynamical systems, with multiple layers of feedback and interaction, and CCM can help identify these more complex causal interactions, particularly reciprocal or bidirectional causality. Because CCM examines the relationships between projections of the time series, we normalized the data to measure the percent change at each time point to account for the vastly different scales of conflict casualties, infant mortality, and GDP. We observed convergence in 80% of countries supporting the hypothesis that conflict causes poverty, and 12% for poverty leading to conflict. However, these results may be skewed by the perfect predictability of conflict in countries that experienced no conflict during the time period under study. Fig. 2 shows an example of convergence to support the hypothesis that conflict causes poverty in Comoros.

While dynamic time warping and convergent cross-mapping can be useful analytic tools, the nature of our case study data is not ideal for these types of methods that look explicitly for point-by-point relationships across the time series. Even though the relationships between conflict and poverty are difficult to quantify, we found they can be reasonably described through qualitative featurization analysis. While conflict and poverty are linked to one another, this phenomenon does not manifest as similar patterns of proportional increases or decreases in values offset in time. Instead, across the countries studied, we saw that rapid increases in conflict or periods of recurring conflict are associated not with similar fluctuations in poverty, but by continually decreasing or statically depressed levels of economic activity and by statically high levels of infant mortality. Similarly, we found that when the conflict ended, we saw decreases in poverty follow. In essence, this illustrates the notion of the conflict and poverty traps, where violence is associated not with rapid declines into poverty, but with sustained levels of minimal development.

Fig. 3 shows an example using the qualitative feature-based approach to analyze the data from Senegal. The top plot indicates GDP in current US$ from 1989 to 2013, the middle plot shows the number of battle related deaths, and the bottom chart is the infant mortality rate. The human-guided qualitative featurization algorithm has divided these data series into important component pieces representing distinct features. From these features, it is evident that there was a period of violent conflict from 1989 to about 2004, with several spikes in the number of casualties. During this same time, infant mortality was consistently high, and GDP was consistently low. However, after 2004, GDP and infant mortality both begin to steadily improve, while conflict remains very limited. Using these features to represent concepts such as “spikes in conflict” and “high infant mortality,” we can identify causal patterns between these more complex features that are not visible in a lower-level comparison of individual time points.

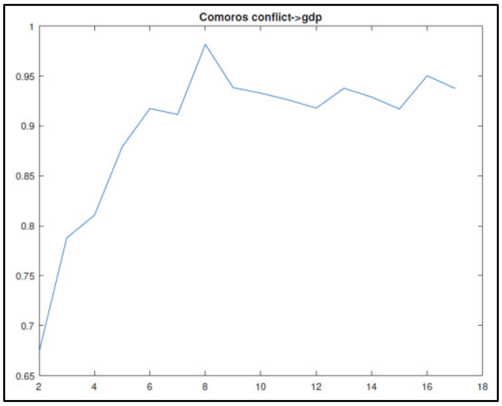

Fig. 2. Results from CCM analysis illustrating convergence indicative of a causal link from conflict to poverty.

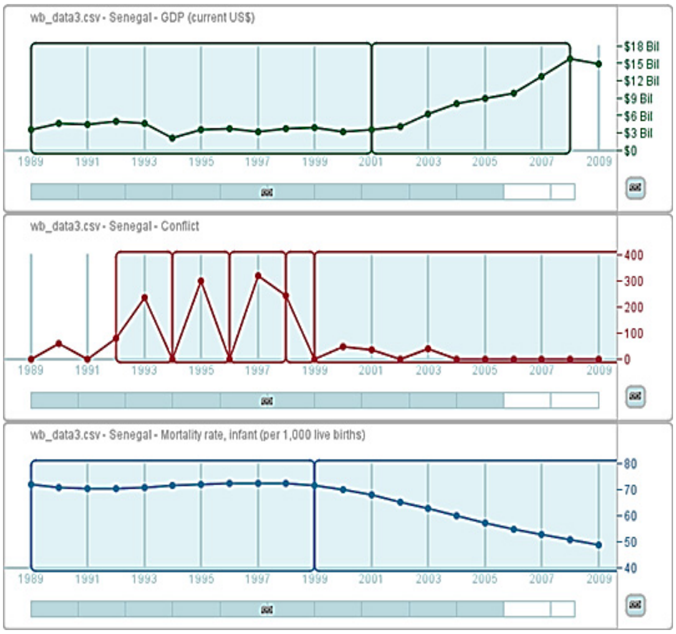

Fig. 3. Qualitative featurization showing the relationships between poverty and conflict.

5. Discussion and conclusions

We have presented several methods—Granger causality, dynamic time warping, convergent cross mapping, and qualitative feature-based analysis—for identifying and (in)validating causal/predictive relationships within observational sociopolicital data, and described some preliminary experimental results analyzing the nature of causal/predictive processes relating to poverty and conflict processes relating to poverty and conflict. Using Granger causality, we were able to achieve some preliminary support for the validation of the causal hypothesis regarding conflict and poverty, and use this to help form another hypothesis—this relationship is likely bidirectional because conflict and poverty Granger cause each other. Using qualitative feature-based analysis, we were able to identify relationships between complex patterns that are difficult to describe in terms of mathematical correlations. Our fundamental conclusion is that none of the exiting techniques are sufficient and that we need a suite of tools, each with its own strengths. Each of these causality analysis approaches helps to clarify the nature of these causal relationships, providing researchers with a variety of techniques to enhance their understanding of causal patterns.

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References

[1] Munck, G. L. (1998). Canons of research design in qualitative analysis. Studies in Comparative International Development, 33, 18-45.
[2] Brady, H. E., Collier, D., and Seawright, J. (2006). Toward a pluralistic vision of methodology. Political Analysis, 14, 353-368.
[3] Harrell, F. E. (2001). Regression modeling strategies: with applications to linear models, logistic regression, and survival analysis. Springer.
[4] Granger, C. W. J. Testing for causality: A personal viewpoint. Journal of Economic Dynamics and Control 2, 329-52. 1980.
[5] Granger, C. W. J. "Investigating causal relations by econometric models and cross-spectral methods." Econometrica 37.424 (1969).
[6] Box, G. P. and Jenkins, G. M. (1970). Time series analysis: forecasting and control. San Francisco, CA: Holden Day.
[7] Freeman, J. R. (1983). Granger causality and the times series analysis of political relationships. Am. Journal of Political Science, 327-358.
[8] Goldthorpe, J. H. (2001). Causation, statistics, and sociology. European Sociological Review, 17, 1-20.
[9] Myers, C. and Rabiner, L. (1981). A level building dynamic time warping algorithm for connected word recognition. Acoustics, Speech and Signal Processing, IEEE Transactions on, 29, 284-297.
[10] Chan, P. and S. Salvador. "Toward Accurate Dynamic Time Warping in Linear Time and Space." Intelligent Data Analysis 11.5 (2007).
[11] Sugihara, G., et al. "Detecting Causality in Complex Ecosystems." Science. (2012).
[12] Robert T.Olszewski. "Generalized Feature Extraction for Structural Pattern Recognition in Time Series Data." Carnegie Mellon Univ. 2001.
[13] Sliva, A. and Neal Reilly, S. "A Big Data Methodology for Bridging Quantitative and Qualitative Political Science Research." Proceedings of the American Political Science Association, August 2014.
[14] Neal Reilly, S. Validation Coverage Toolkit for HSCB Models. R09005-03. 2010. Cambridge, MA, Charles River Analytics Inc.
[15] Neal Reilly, W. S., A. Pfeffer, and J. Barnett. "A Metamodel Description Language for HSCB Modeling." Advances in Cross-Cultural Decision Making. Ed. D. Schmorrow and D. Nicholson. CRC Press, 2010.
[16] Neal Reilly, W. S., et al. "A Computational Toolset for Socio-Cultural Data Exploration, Model Refinement, and Model Validation". HSCB Focus Chantilly, VA: 2011.
[17] Collier, Paul; Elliott, V. L.; Hegre, Håvard; Hoeffler, Anke; Reynal-Querol, Marta; Sambanis, Nicholas. (2003). Breaking the Conflict Trap: Civil War and Development Policy. Washington, DC: World Bank and Oxford University Press.
[18] Collier, P. and Hoeffler, A. (2004). "Greed and Grievances in Civil Wars." Oxford Economic Papers 56.
[19] Braithwaite, Alex, Niheer Dasandi, and David Hudson (2014). "Does poverty cause conflict? Isolating the causal origins of the conflict trap." Conflict Management and Peace Science.
[20] Djankov, S. and Reynal-Querol, M. (2008). "Poverty and Civil War: Revisiting the evidence", CEPR No. 6980.
[21] Themnér, Lotta & Peter Wallensteen (2014) Armed Conflict, 1946-2013. Journal of Peace Research 51(4).
[22] The World Bank. World Development Indicators. 2013.